An Acquisition of Fuzzy Rules for Mobile Robot Using Fuzzy Classifier Systems

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Abstract— **We had presented an automatic generation method of fuzzy rules using hyper-cone membership functions by fuzzy classifier system (FCS), and applied to the inverted pendulum control. However, it is considered that the FCS can be applied to on-line learning of autonomous robots, etc.. In this paper, we tried that the presented FCS was applied to simulation of a mobile robot. Also, two methods which genetic operations were improved were used in order to aim at the application to the real machine.**

Keywords— **Fuzzy Classifier System, Fuzzy Rule Generation, Genetic Algorithm, Mobile Robot.**

I. Introduction

Fuzzy classifier systems (FCSs) applying the Michigan approach type genetic algorithms (GAs) are proposed [1],[2]. These methods are composed of compact systems, because GA is done in one fuzzy system.

We had presented an automatic generation method of fuzzy rules using hyper-cone membership functions by FCS [3]. In this method, the hyper-cone membership function[4][5] is expressed by a kind of radial basis function, and its fuzzy rule can be flexibly located in input and output spaces. We applied this method to fuzzy rules generation of the inverted pendulum control. However, it is considered that the FCS can be applied to on-line learning of autonomous robots, etc.. In this paper, we try that the presented FCS is applied to simulation of a mobile robot. Also, two methods which genetic operations were improved are used in order to aim at the application to the real machine.

II. Fuzzy Classifier System Using Hyper-Cone Membership Functions

A. *Fuzzy Rules Using Hyper-Cone Membership Functions*

A.1 Hyper-Cone Membership Function

In this paper, we use fuzzy systems which expand to the simplified fuzzy reasoning. In this method, we give fuzzy rule R^i as below:

$$R^i : \text{if } \boldsymbol{x} \text{ is } A_i \text{ then } \boldsymbol{y} \text{ is } \boldsymbol{b}_i,\ \ i = 1, 2, \cdots, n \qquad (1)$$

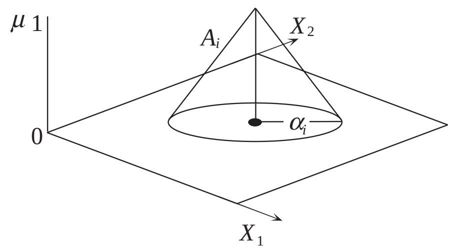

Fig. 1. Shape of Hyper-Cone Membership Function ($l = 2$)

where i is rule number, n is the number of rules, $\boldsymbol{x}$ and $\boldsymbol{y}$ are the input and output vectors, respectively. A_i is fuzzy subsets, and $\boldsymbol{b}_i$ is the real valued vector. In this method, fuzzy subsets A_i is defined by a hyper-cone membership function. In this fuzzy system, since there are n fuzzy rules, n hyper-cone membership functions are located in input and output each space.

The hyper-cone membership function $\mu_{A_i}(\boldsymbol{x})$ of A_i is defined by Eqs.(2) and (3).

$$\mu_{A_i} : A_i \to [0, 1] \qquad (2)$$

$$\mu_{A_i}(\boldsymbol{x}) = \left(1 - \frac{\|\boldsymbol{x} - \boldsymbol{a}_i\|}{\alpha_i}\right) \vee 0 \qquad (3)$$

where $\boldsymbol{a}_i$ and α_i are the center vector and the radius of the fuzzy subsets A_i. $\boldsymbol{a}_i$ is defined as follow,

$$\boldsymbol{a}_i = \begin{bmatrix} a_{i1} & a_{i2} & \cdots & a_{il} \end{bmatrix}^{\mathrm{T}} \qquad (4)$$

The membership function μ_{A_i} has a grade 1.0 at the center $\boldsymbol{a}_i \in \boldsymbol{R}^l$, and the membership value decreases in proportion to the distance from the center $\boldsymbol{a}_i$. At the circumference of this sphere, a grade has 0.0. Fig.1 shows the hyper-cone membership function in case of $l = 2$ (l is the number of inputs).

In the consequence part of the fuzzy rule R^i, the real valued vector $\boldsymbol{b}_i$ is output values in m dimensional output space, and defined following equation.

$$\boldsymbol{b}_i = \begin{bmatrix} b_{i1} & b_{i2} & \cdots & b_{im} \end{bmatrix}^{\mathrm{T}} \qquad (5)$$

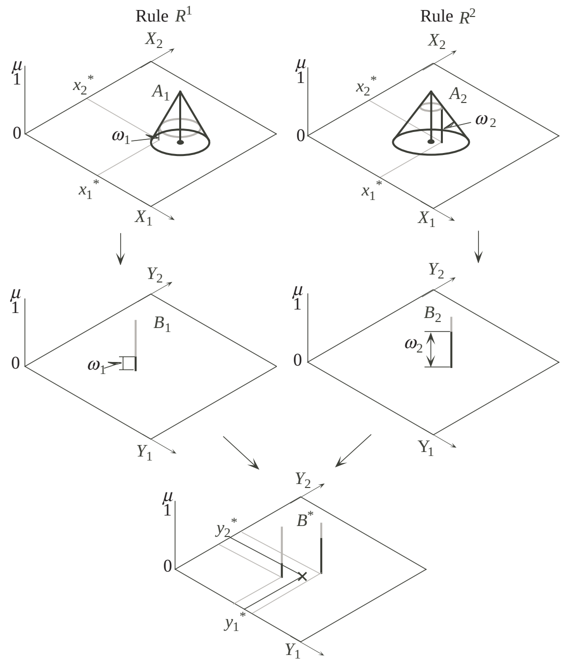

Fig. 2. An Example of the Reasoning Method

A.2 Reasoning Method

If the input vector $\boldsymbol{x}^*$ is provided to fuzzy systems, the real output value $\boldsymbol{y}^*$ is calculated following method. The truth value ω_i of a rule R^i for input vector $\boldsymbol{x}^*$ is calculated by Eq.(3). In other words, the membership value is the truth value ω_i.

$$\omega_i = \mu_{A_i}(\boldsymbol{x}^*) \tag{6}$$

Output $\boldsymbol{y}^*$ is given by Eq.(7).

$$\boldsymbol{y}^* = \frac{\displaystyle\sum_{i=1}^{n} \omega_i \boldsymbol{b}_i}{\displaystyle\sum_{i=1}^{n} \omega_i} \tag{7}$$

Fig.2 shows an example of the reasoning in the case of $l = 2,\ m = 2,\ n = 2$.

In our method, all rules can not always cover input space. Therefore, there often exists spaces whose membership grade for input $\boldsymbol{x}^*$ is zero. If an input vector $\boldsymbol{x}^*$ is determined in such a space, a rule R^ϕ to be fired is defined by

$$d_i = \|\boldsymbol{x}^* - \boldsymbol{a}_i\| - \alpha_i \tag{8}$$

$$R^\phi = \left\{ R^i \,|\min\{d_i\} \right\} \tag{9}$$

Eqs.(8) and (9) mean that only the rule having the membership function closest to input vector $\boldsymbol{x}^*$ is fired with $\omega_\phi = 0.0$. In case of R^ϕ, $\boldsymbol{y}^*$ is given values of the real valued vector $\boldsymbol{b}_\phi$.

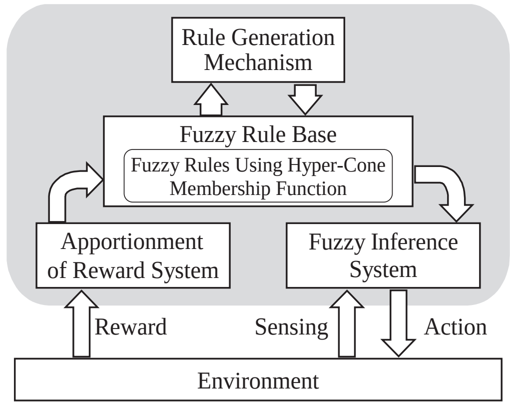

Fig. 3. Fuzzy Classifier System

B. Fuzzy Classifier System Using Hyper-Cone Membership Functions

FCS consists of four blocks as shown in Fig.3. In this method, fuzzy systems using hyper-cone membership functions are used. Fundamental operations of FCS are as follows.

[Fuzzy Rule Base]

There existed n fuzzy rules based on hyper-cone membership functions.

[Fuzzy Inference System]

Senses (inputs) are received from an environment, and fuzzy rules which suit these senses are chosen from the Fuzzy Rule Base. Then, fuzzy reasoning described in before section is carried out from those rules, and actions (outputs) to the environment are decided.

[Apportionment of Credit System]

In the Apportionment of Credit System, rewards are provided from the environment to the FCSs for actions. In other words, reward is an evaluation for the fuzzy system. Also, rewards are distributed to each rule as a credit. The credit is an evaluation of each rule, and higher the rule contributes to obtain the reward, higher the evaluation of the rule increases. In this method, the credit cf_i of each rule is provided following method. When there are J actions in one trial, a reward $re_j (j = 1, 2, \ldots, J)$ is given in each action. The credit $cf_i (i = 1, 2, \ldots, n)$ is given from the reward in proportion to the truth value of the rule as follows:

$$cf_i = \sum_{j=1}^{J} \frac{\mu_{ij}}{g_j} \times re_j \tag{10}$$

$$g_j = \sum_{i=1}^{N} \mu_{ij} \tag{11}$$

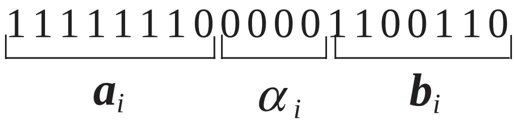

Fig. 4. Example of Chromosome

where μ_{ij} is the truth value of fuzzy rule R^i in reasoning action (output) j.

[Rule Generation Mechanism]

New rules are generated based on credit cf_i by GA. A coding of one rule in this GA is done as one individual. Therefore, each credit is given a fitness of each individual. Also, population is composed of n individuals because there are n fuzzy rules. Genetic parameters of fuzzy rule R^i are as follow

- Center coordinate $\boldsymbol{a}_i$ of fuzzy subset A_i,
- Radius α_i of fuzzy subset A_i, and
- Real valued vector $\boldsymbol{b}_i$ in consequence part of fuzzy rule R^i.

These parameters are coded as one chromosome like Fig.4.

This method is used genetic operations (see Fig.5) based on the simple GAs. The procedure of genetic operations is as follows:

[Step1] An initial population is randomly produced. Also, the fitness (the credit cf_i) of each individual is calculated.

[Step2] We produce the population of the next generation by following operations until a population size n is completed.

Selection: Two individuals (rules) are selected by the roulette wheel model.

Crossover: Two individuals cross each other. This method is used one point crossover.

Mutation: Each gene is mutated by a mutation rate.

Reproduction: Place new offspring in a new population.

[Step3] Carrying out the new fuzzy system, and the credit cf_i of each rule is calculated. In other word, fitness values are provided.

[Step4] If a prespecified stopping condition is not satisfied, return to Step2. If this condition is satisfied, this process ends. In this paper, the stopping condition is the number of generations.

III. Improvement of Genetic Operation

In the proposed FCS in the section 2, all fuzzy rules of the fuzzy system are generated by genetic operations. Therefore, feature of the performance in the previous generation may not be inherited in a new fuzzy system of next generation. Consequently, the evaluation of the performance in next generation is become badly. Also, similar rules are generated, because this method have many opportunities to chose rules with high credit value (fitness) by the selection operation. For these problems, we introduce two methods to FCS. In these methods, only one rule is generated by GA operation, and renewed in each generation.

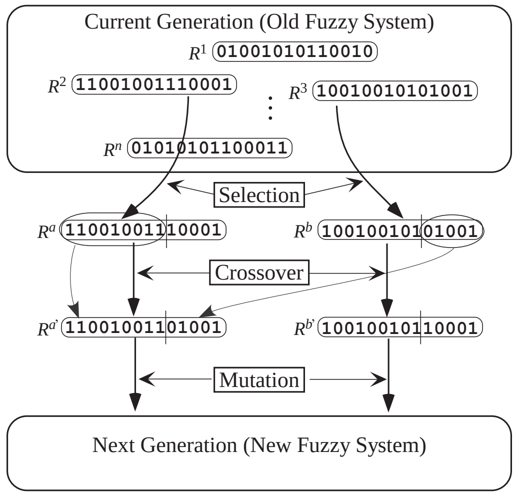

Fig. 5. Genetic Operations

Method 1

In this method, one rule having smallest credit (fitness) cf_i is selected, and replaced with newly generated rule. In Method 1, Step2 in "Rule Generation Mechanism" of FCS is changed as follow.

[Step2] Only one time carries out next operation.

Selection: Two individuals (rules) are selected by the roulette wheel model.

Crossover: Two individuals cross each other. This method is used one point crossover.

Mutation: Each gene of two offspring is mutated by a mutation rate.

Reproduction: One offspring is randomly chosen from the two offspring. This offspring is replaced with an individual having smallest credit (fitness) cf_i.

Method 2

In this method, GA operations are carried out using randomly selected two individuals. In Method 2, Step2 in "Rule Generation Mechanism" of FCS is changed as follow.

[Step2] Only one time carries out next operation.

Selection: Two individuals (rules) are randomly selected. In these individuals, the individual with smaller credit value is I_S.

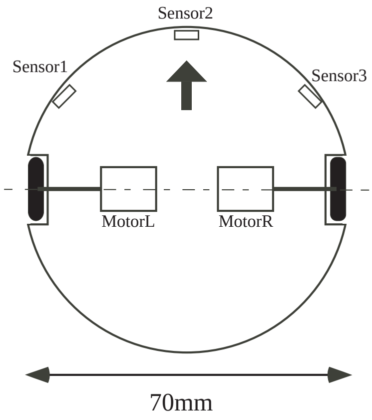

Fig. 6. Mobile Robot

Crossover: Two individuals cross each other. This method is used one point crossover.

Mutation: Each gene of two offspring is mutated by a mutation rate.

Reproduction: One offspring is randomly chosen from the two offspring. This offspring is replaced with an individual I_S.

IV. Application to Mobile Robot

A. Simulation Model

We generated fuzzy rule for the mobile robot by the presented method. Fig.6 and Fig.7 are showed the mobile robot and its simulation environment. The robot has three range sensors (Sensor1, Sensor2 and Sensor3), and left and right motors (MotorL and MotorR) are controlled. Therefore, generated fuzzy systems are three inputs and two outputs problem. Also, the robot runs circumference of ow ($= 150$mm) width in a square field of tw ($= 700$mm) on a side.

B. Setting of GA

The reward re_j for the FCSs is given by evaluating the performance of the robot. Therefore, the reward re_j is calculated using a reward $re1_j$ for moving distance of the robot and a reward $re2_j$ when the robot reached each corner.

$$re1_j = \begin{cases} d_l + d_r & d_l + d_r > 0 \\ (d_l + d_r) \times (-2) & d_l + d_r \leq 0 \end{cases} \tag{12}$$

$$re2_j = \begin{cases} 20000 & \text{when the robot reached corner} \\ 0 & \text{otherwise} \end{cases} \tag{13}$$

$$re_j = re1_j + re2_j \tag{14}$$

where d_l and d_r are distances in which left and right wheels moved.

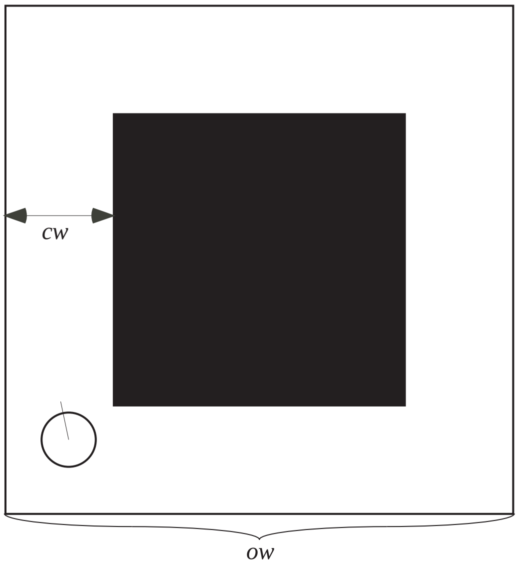

Fig. 7. Simulation Environment

TABLE I
Average and Maximum of Total Reward Value

	Original Method	Method 1	Method 2
Average	143587.00	51539.55	154795.41
Maximum	236368.12	236606.55	236898.40

We set the number of rules (the population size) $n = 10$. The crossover rate was 25%, the mutation rate was 3.0%, and the number of generation was 1000.

C. Simulation Result

We tried 20 times for different initial populations in each method, and obtained fuzzy rule sets. Table I shows average and maximum values of total reward value re_T. re_T is given by Eq.(15)

$$re_T = \sum_{j=1}^{J} re_j \tag{15}$$

In the table, the Original Method and the Method 2 show the almost equal results, and the average value of Method 2 has lowered. Actually, fuzzy systems which the robot rotates around the circumference like the Fig.8 have been obtained the Original Method and the Method 2. However, in the Method 1, there were many cases that fuzzy systems which robot collides with wall were obtained.

Fig.9 shows graphs of total reward value re_T of the Original Method and the Method 2 for gener-

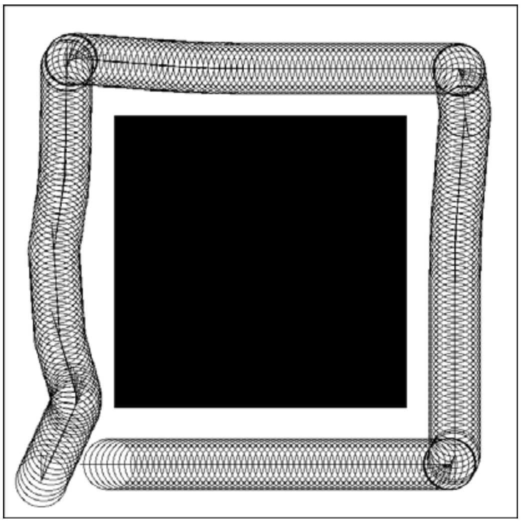

Fig. 8. Simulation Result

ations. From this figure, in the Method 2, there is no remarkable fluctuation of the total reward like the Original Method, because the structure of fuzzy systems in next generation greatly dose not change.

V. Conclusions

In this paper, we applied FCS using hyper-cone membership function to simulation of the mobile robot. Also, we introduced two methods using another genetic model, and each method was compared with the original method. As future problems, it is necessary to consider FCS suitable for behavior acquisition of the mobile robot.

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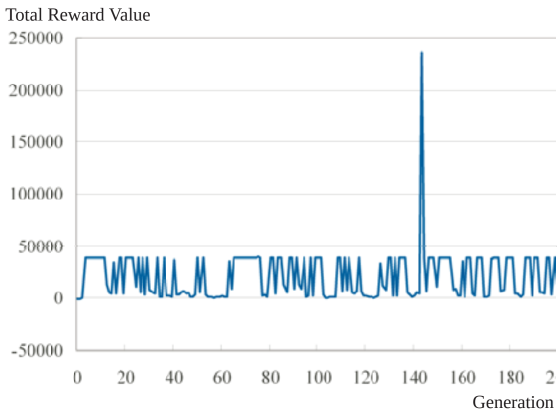
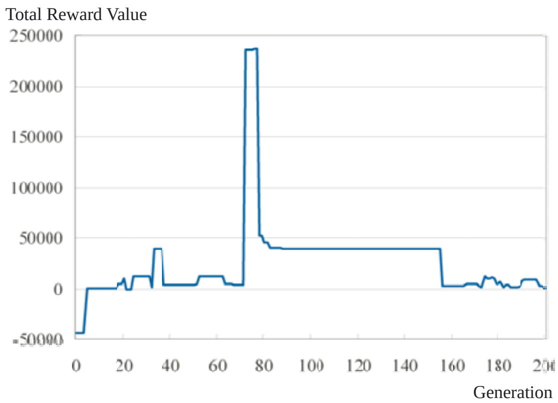


(a) Original Method



(b) Method 2

Fig. 9. Graphs of Total Reward Value for Generations